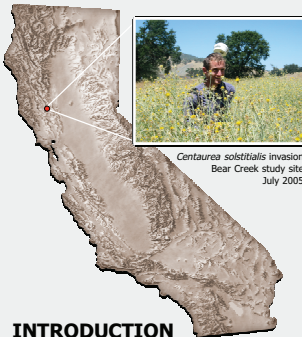


Mapping the distribution & abundance of the invasive weed *Centaurea solstitialis* using hyperspectral imagery

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INTRODUCTION

Effectively managing exotic plant invasions requires accurate data on the abundance and distribution of the invader across the landscape. Of particular importance is the ability to detect small, incipient populations before they become large, persistent invasions¹. Remotely sensed data is potentially the best way to collect these data because such data can be rapidly gathered over large areas, across management and habitat boundaries, with high spatial resolution. Here we test the ability of hyperspectral imagery to map the distribution and abundance of the invasive plant *Centaurea solstitialis* L. (Asteraceae) across a 21 km² watershed in a California grassland.

METHODS

Image acquisition and preparation.

Hyperspectral imagery was gathered over our study site in late July, 2005 (peak biomass for *C. solstitialis*) using a CASI2 pushbroom imager (spectral resolution: 450-970nm, 48 bands, 5.8nm channel width; spatial resolution 2m x 2m) (Figure 1). Using ENVI v.4.1, we applied 2 principle components analyses to segregate noise from signal and retained only informative data for subsequent processing (15 PCA bands, Figure 2).



Figure 1. Hyperspectral image of study site

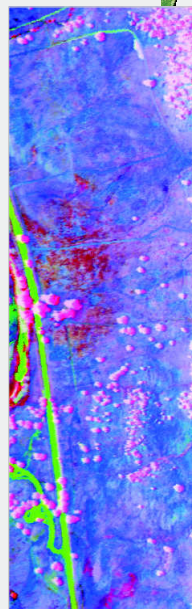


Figure 2. Noise-whitened version of image following 2 PCAs

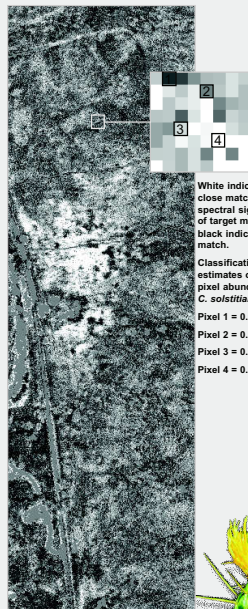


Figure 3. Gray-scale image with sub-pixel abundance values for *Centaurea solstitialis*

METHODS (cont.)

Image analysis. Every material reflects incoming solar radiation differently and so produces a unique spectral signature. Consequently, every pixel has a spectral signature that is a linear combination of the spectral signatures of the materials contained within it. We used a spectral linear unmixing algorithm² to search for *C. solstitialis* in each 2m x 2m pixel and estimate its per-pixel abundance.

Image validation & statistical analysis. We used a GPS unit with sub-meter accuracy to navigate to 188 randomly located validation plots, equal in size to a single pixel (2m x 2m). We measured foliar canopy cover and aboveground biomass (dried at 70°C, 48h) of *C. solstitialis* in each validation plot.

Classification accuracy & precision. Accuracy was defined as the percentage of validation plots that were properly classified as invaded or uninvaded. Precision was defined as the ability of the classification to quantify *C. solstitialis* abundance and we assessed the classification's performance using regression and both measures of *C. solstitialis* abundance (canopy cover and aboveground biomass). We used logistic regression to identify the lowest abundance threshold for reliable identification.

Table 1. Summary of the accuracy of the classification.

Classification	Field	
	Present	Absent
Present	72	0
Absent	10	106
Accuracy	88%	100%
Overall Accuracy	95%	

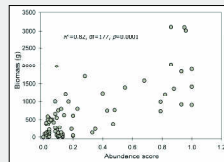


Figure 7. Ability of classification to quantify biomass cover of target weed

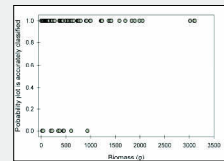


Figure 8. Detection threshold

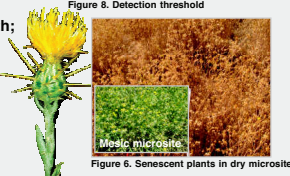


Figure 6. Senescent plants in dry microsite

RESULTS AND DISCUSSION

The result is a gray-scale image in which abundance values, estimated to the nearest half a percent, are embedded in each pixel (Figure 3). We collapsed the abundance data in Figure 4 into categories most useful to land managers and then color-coded them for ease of visual interpretation (Figure 5).

Overall accuracy was 95% (Table 1). The classification was always correct when it indicated that *C. solstitialis* was present; however, it failed to detect *C. solstitialis* in 10 cases. *C. solstitialis* abundance in misclassified pixels was variable but in some cases very high (367g \pm 86g SE, range: 17-935g), indicating that the failure was not attributable to a weak spectral signal driven by extremely low quantities of the plant. Rather, in these cases the plants were growing in particularly xeric microsites and were well into senescence at the time of image acquisition (Figure 6) and water stress is known to alter spectral signature³.

Unfortunately, plant physiological condition, which drives the change in spectral signature, is likely to vary significantly over the spatial scales relevant to remote sensing. A solution to this problem is to identify *a priori* the unique spectral signature for the plant under different environmental or phenological conditions (i.e., the target species will have more than one spectral signature). While this is time consuming, errors of omission are especially problematic in invasive species management and such additional effort is likely justified.

The classification predicted canopy cover rather poorly ($R^2=0.51$, $df=186$, $p=0.001$) but did a better job of predicting biomass (Figure 7). With the exception of the misclassified pixels, the classification was able to reliably detect *C. solstitialis* with as little as 1% cover and 5g of aboveground biomass (Figure 8). Detecting exotic plants at low levels of abundance over a large spatial extent, is an invaluable tool in proactively managing incipient invasions.

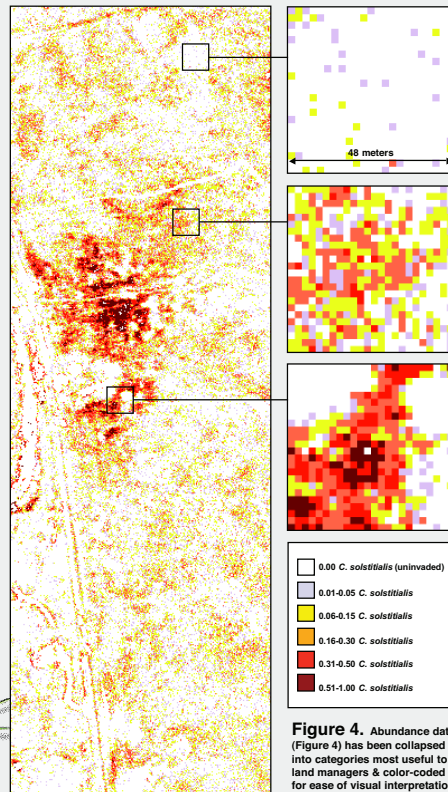


Figure 4. Abundance data (Figure 3) has been collapsed into categories most useful to land managers & color-coded for ease of visual interpretation.

LITERATURE CITED

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3. Mundt, J. J. et al. 2005. *Remote Sensing of Environment* 96:509-517.